

# Top cross section measurement in the lepton+jets channel with $b$ -tagging at DØ

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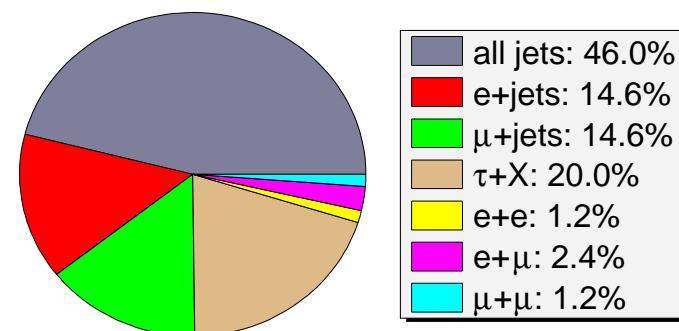
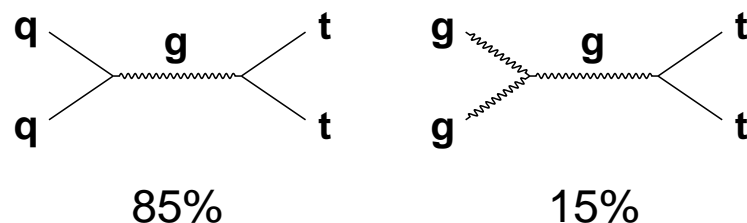
W&C Seminar, September 10, 2004

## Motivation

- the knowledge on top quark properties from Run I data has been severely affected by the small statistics available. This should not be an issue in Run II with the large anticipated data samples
- the measurement of the  $t\bar{t}$  cross section is a good test of perturbative QCD
- New Physics may manifest itself in top production (e.g.  $t\bar{t}$  resonance) or decay (e.g.  $t \rightarrow H^+ b$ )
- studies of top production are important in the LHC perspective where  $t\bar{t}$  is a dominant background to many searches for new physics

## $t\bar{t}$ production in lepton+jets mode

- at the Tevatron, top quarks are mostly produced in pairs ( $t\bar{t}$ )

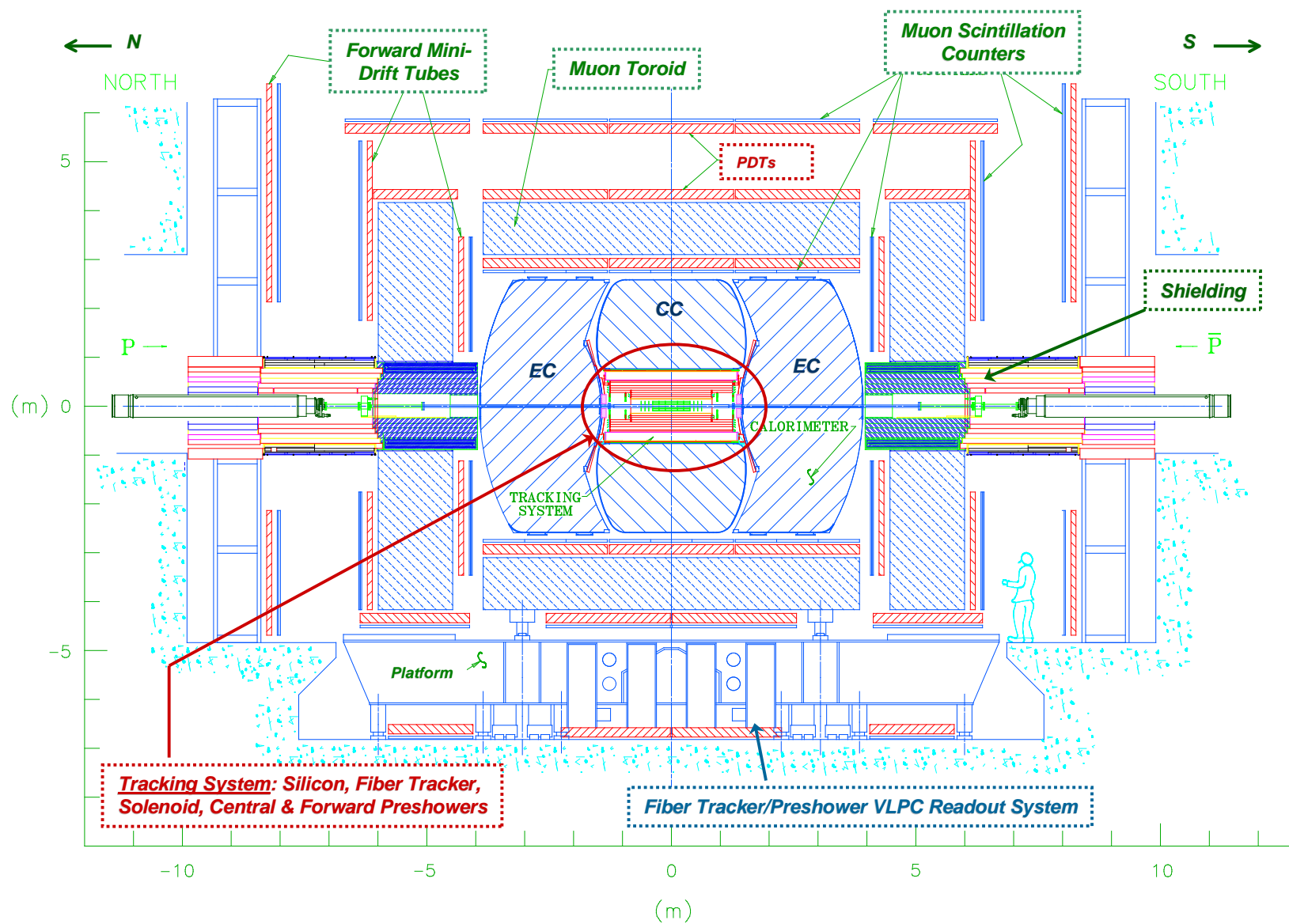


- in the Standard Model, top almost always decays to  $Wb$
- as  $W$  may decay hadronically or leptonically, there are dilepton, lepton+jets, and all jets  $t\bar{t}$  channels

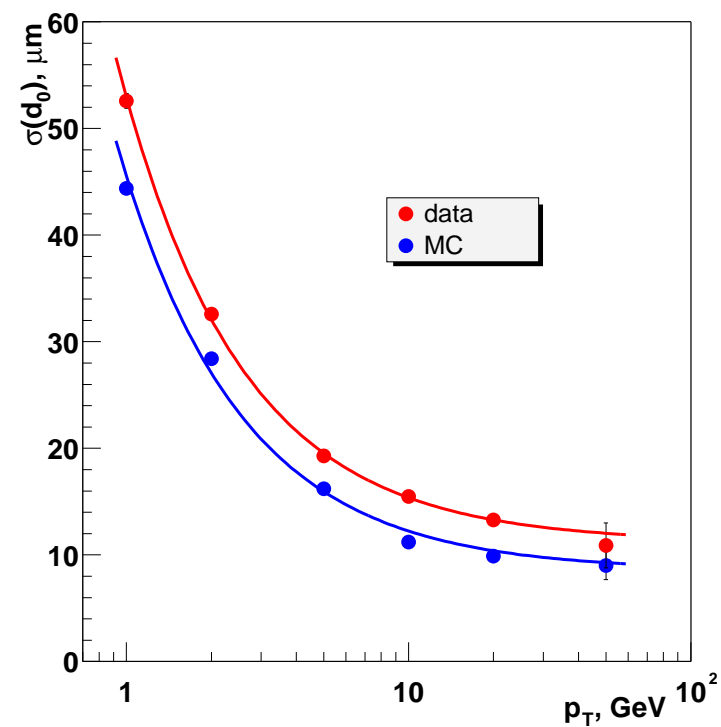
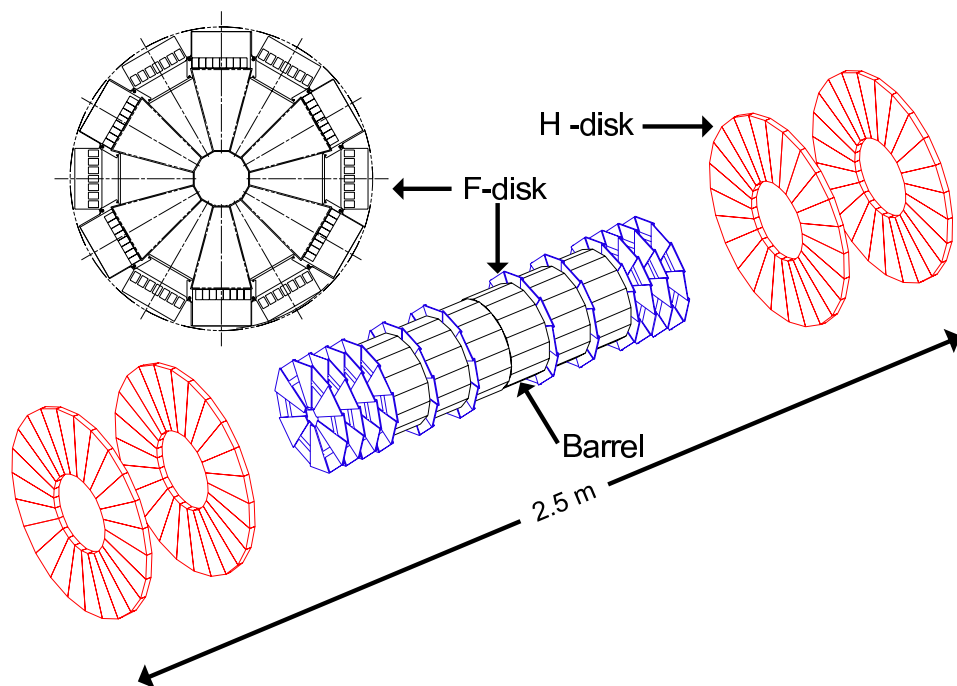
- look at the **lepton+jets channel**:
  - large statistics compared to dileptons
  - clear signature compared to all jets

- the purity of the lepton+jets channel is not that high as for dileptons, need a method to increase the fraction of the signal
- one approach used since Run I is the topological selection
- in the present analysis use  **$b$ -tagging** ( $b$ -jet identification)

# DØ detector in Run II

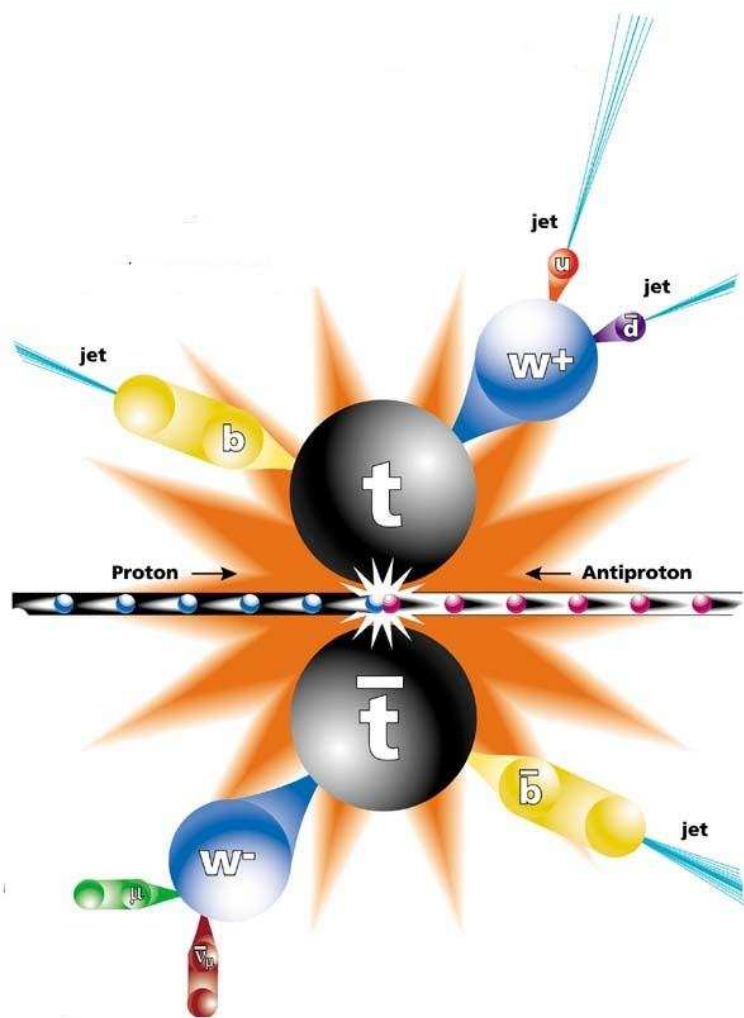


## Silicon Microstrip Tracker



impact parameter resolution in data:  $\sigma(d_0) = 11 + 42 \text{ GeV}/p_T \mu\text{m}$

## Event selection



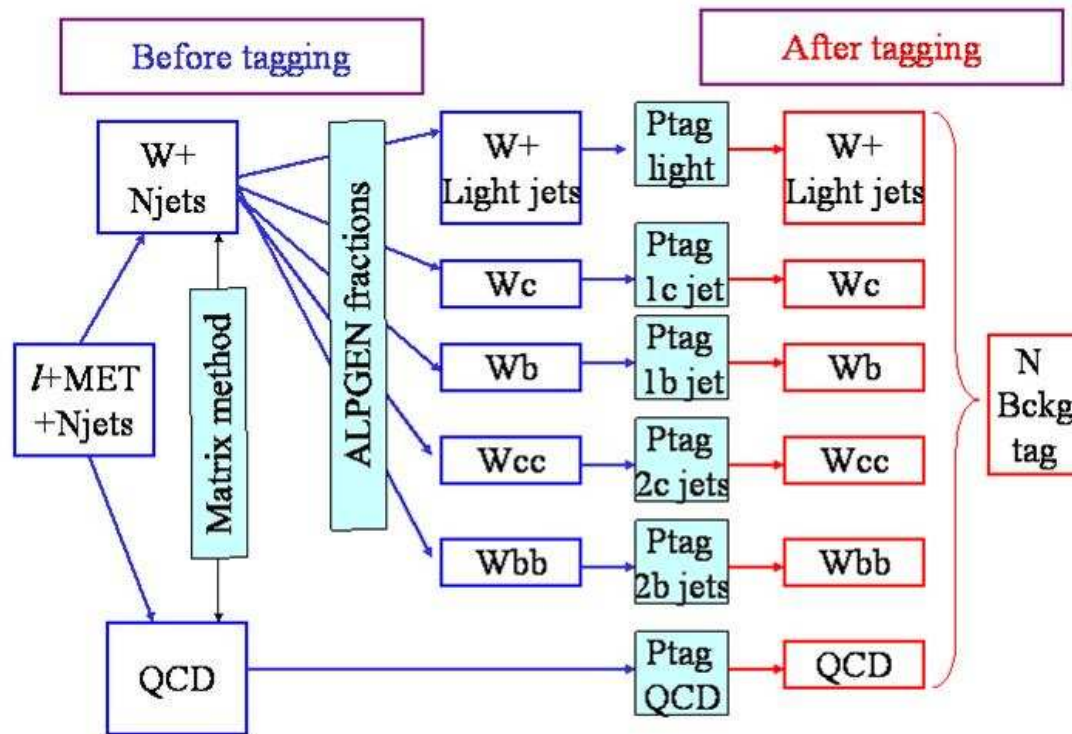
### • The signature:

- a lepton+jet trigger
- a  $p_T > 20$  GeV isolated lepton within  $|\eta| < 1.1$  ( $e$ ) or  $|\eta| < 2$  ( $\mu$ )
- high missing  $E_T$  (20 GeV for  $e$ +jets, 17 GeV for  $\mu$ +jets)
- at least three jets with  $p_T > 15$  GeV,  $|\eta| < 2.5$

### • Additional requirements:

- high quality primary vertex ( $N_{tr} \geq 3$ ,  $|z| < 60$  cm)
- triangular cut in  $\Delta\phi(l, \cancel{E}_T)$  vs  $\cancel{E}_T$
- second high  $p_T$  lepton isolation veto

## Background estimation



- subtract small backgrounds (single top,  $VV$ ,  $Z \rightarrow \tau^+\tau^-$ ) using known cross sections
- calculate QCD (non- $W$ ) contribution with matrix method
- separate  $W$  from  $t\bar{t}$  using difference in their event tagging probabilities
- $t\bar{t}$  signal is observed as an excess in tagged events with  $\geq 3$  jets over background prediction

$$N = N_{t\bar{t}} + N_W + N_{QCD} + N_S$$

$$N^{tag} = N_{t\bar{t}}^{tag} + N_W^{tag} + N_{QCD}^{tag} + N_S^{tag}$$

## QCD background estimation: matrix method

- define a “loose” sample by relaxing the lepton quality cuts
- derive the QCD fraction from the measured probabilities for a “true” lepton ( $\epsilon_{W+t\bar{t}}$ ) and a “fake” lepton ( $\epsilon_{QCD}$ ) to go from the loose to the tight sample

$$\begin{aligned} N^{loose} &= N_{QCD}^{loose} + N_{W+t\bar{t}}^{loose} \\ N^{tight} &= \epsilon_{QCD} N_{QCD}^{loose} + \epsilon_{W+t\bar{t}} N_{W+t\bar{t}}^{loose} \end{aligned}$$

- **method I:** apply matrix method to the untagged sample, then

$$N_{QCD}^{tag} = P_{QCD} N_{QCD}$$

$P_{QCD}$ : probability to tag a QCD event, measured in data

- **method II:** apply matrix method directly to the tagged sample

- **$e$ +jets:** QCD dominated by jets faking electrons
  - both methods are shown to give compatible results, use method I as having superior statistical precision
- **$\mu$ +jets:** QCD dominated by muons from semileptonic heavy flavor decays
  - have to use method II in absence of a reliable estimation for  $P_{QCD}$  in this case (QCD HF composition is different for low and high  $E_T$ )
  - **caveat:** smaller number of events on tagged sample leads to relatively large statistical error on  $N_{QCD}^{tag}$



## Event tagging probabilities

- this is the core of the analysis: separation of  $t\bar{t}$  from the  $W$ +jets background is based on difference between their event tagging probabilities
- use kinematics of events from Monte Carlo
- obtain tagging probabilities on data, parameterize, and apply to jets in Monte Carlo in form of **tag rate functions**  $\epsilon_J$  according to relevant jet flavors ( $J = b, c, \text{light}$ ):

**probability to have no tags:**  $P_n^{NT} = \langle \prod_{k=1}^n (1 - \epsilon_{J_k}(E_{Tk}, \eta_k)) \rangle$

**probability to have one tag:**  $P_n^{ST} = \langle \sum_{m=1}^n \epsilon_{J_m}(E_{Tm}, \eta_m) \prod_{k \neq m} (1 - \epsilon_{J_k}(E_{Tk}, \eta_k)) \rangle$

**probability to have  $\geq 2$  tags:**  $P_n^{DT} = 1 - P_n^{NT} - P_n^{ST}$

- probabilities averaged over MC samples implementing relevant corrections that might affect event topology (e.g. trigger efficiency)

## Calculation of tagging efficiencies

- general approach: begin with quantities measured in data, convert them to  $\epsilon_J$  using scale factors ( $SF$ ) derived on Monte Carlo

$b$ -tagging efficiency:  $\epsilon_b = \epsilon_b^{tagg} \epsilon_{b \rightarrow \mu}^{data} SF_{b \rightarrow \mu}^b$

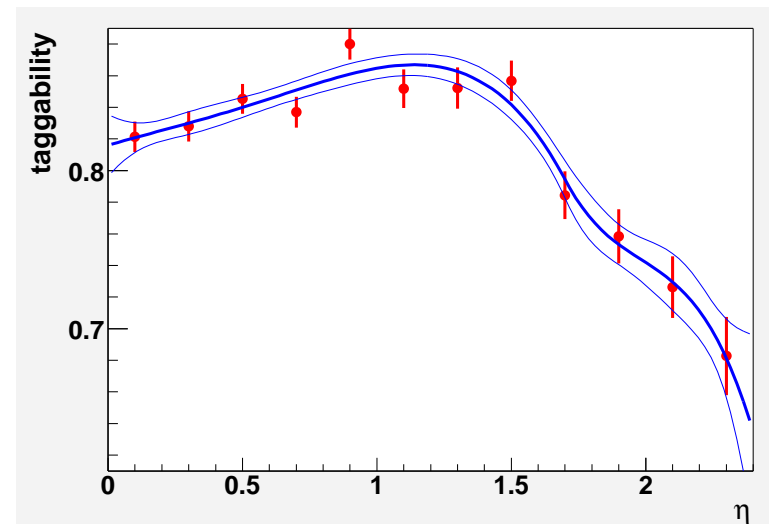
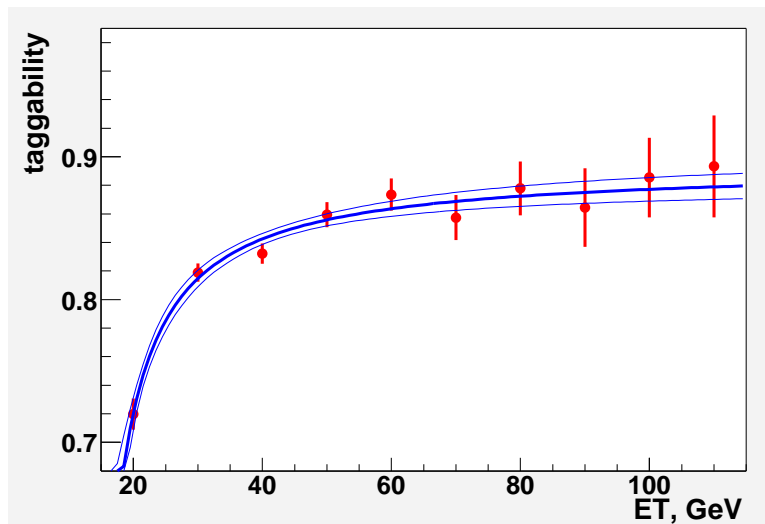
$c$ -tagging efficiency:  $\epsilon_c = \epsilon_c^{tagg} \epsilon_{b \rightarrow \mu}^{data} SF_{b \rightarrow \mu}^c$

mis-tagging rate:  $\epsilon_l = \epsilon_l^{tagg} \epsilon_{neg}^{data} SF_l$

- $\epsilon_J^{tagg}$ : taggability (probability for a jet to be taggable) measured in data and corrected for heavy flavor jets using factors derived on Monte Carlo
- $\epsilon_{b \rightarrow \mu}^{data}$ :  $b$ -tagging efficiency measured in data for jets with a muon inside
- $\epsilon_{neg}^{data}$ : negative tagging rate measured on data

## Taggability

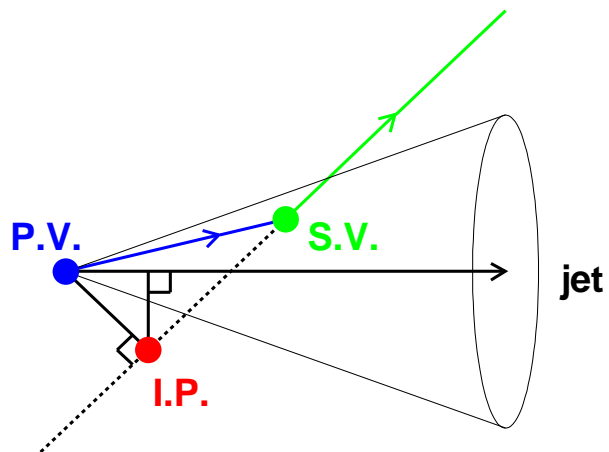
- only a jet that satisfies certain requirements on the number and minimum  $p_T$  of tracks associated with it can be tagged. These jets are called “taggable”
- **taggability**: the probability for a jet to be taggable
- the idea is to largely decouple the tagging efficiency from issues related to tracking inefficiencies and/or calorimeter noise problems
- taggability depends on event sample and is not fully modeled by Monte Carlo



taggability derived on preselected  $e$ +jets sample

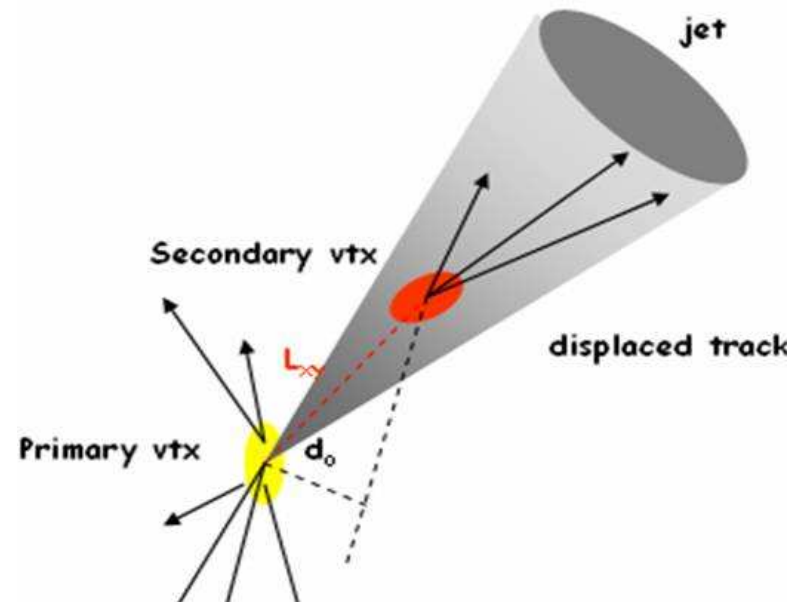
## Lifetime $b$ -tagging methods

### Counting Signed Impact Parameter (CSIP)



- count the number of tracks with large positive DCA significance  $S$
- jet is positively tagged if it has
  - at least two tracks with  $S > 3$ , or
  - at least three tracks with  $S > 2$

### Secondary Vertex Tagger (SVT)



- explicitly reconstruct 3d vertices out of tracks in track-jets using build-up algorithm
- jet is tagged as a  $b$ -jet if the signed decay length significance  $L_{xy} > 7$

## b-tagging efficiency estimation: System 8

- measure  $b$ -tagging efficiency in data for jets with a muon inside
- have two samples with different heavy flavor fractions (increased by tagging the away jet)
- tag jets with two independent tagging algorithms: lifetime tag (LT = CSIP, SVT) and soft lepton tag (SLT = a muon with  $p_T^{rel} > 0.7$  GeV inside a jet)

$$n = n_b + n_l$$

$$p = p_b + p_l$$

$$n^{LT} = n_b \epsilon_{btag}^{LT} + n_l \epsilon_{non-btag}^{LT}$$

$$p^{LT} = p_b \epsilon_{btag}^{LT} + p_l \epsilon_{non-btag}^{LT}$$

$$n^{SLT} = n_b \epsilon_{btag}^{SLT} + n_l \epsilon_{non-btag}^{SLT}$$

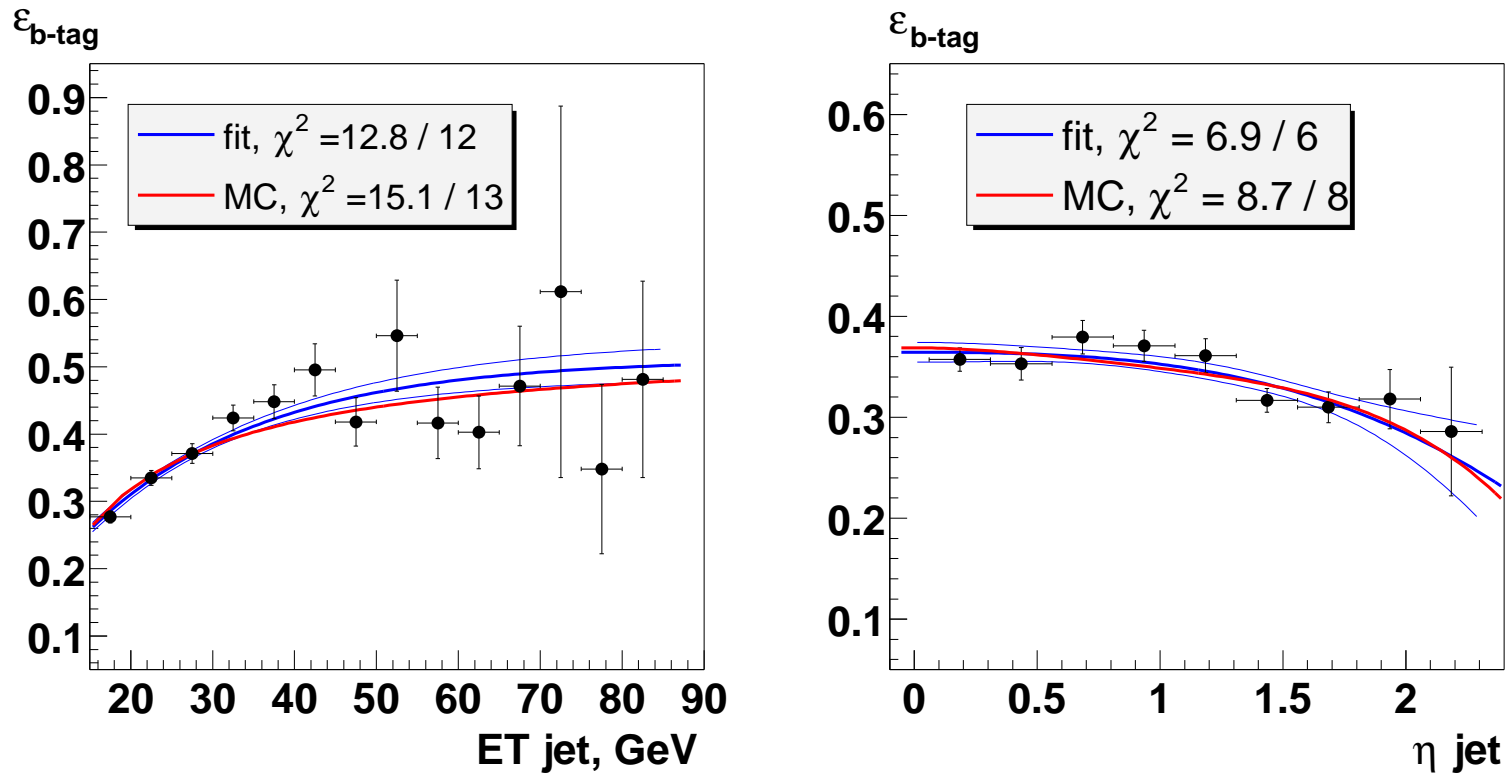
$$p^{SLT} = p_b \epsilon_{btag}^{SLT} + p_l \epsilon_{non-btag}^{SLT}$$

$$n^{both} = n_b \epsilon_{btag}^{LT} \epsilon_{btag}^{SLT} + n_l \epsilon_{non-btag}^{LT} \epsilon_{non-btag}^{SLT}$$

$$p^{both} = p_b \epsilon_{btag}^{LT} \epsilon_{btag}^{SLT} + p_l \epsilon_{non-btag}^{LT} \epsilon_{non-btag}^{SLT}$$

- dominant sources of systematics:
  - assumption on decorrelation between LT and SLT
  - assumption on independence of the  $b$ -tagging probability on whether or not the away jet is tagged

## $b$ -tagging efficiency in data



$b$ -tagging efficiency in data (CSIP), similar efficiency measured for SVT

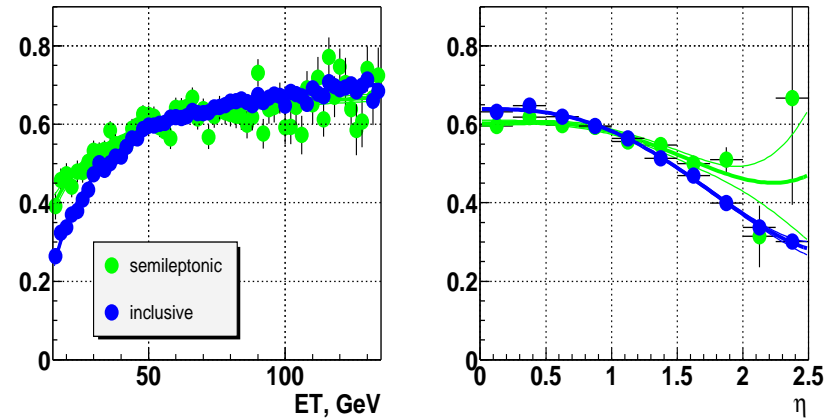
- the shape of the  $b$ -tagging efficiency is predicted by Monte Carlo
- the absolute value of the Monte Carlo prediction on the plot is normalized to data
- use the error band of the data fit to estimate the error on the  $b$ -tagging efficiency

## $b, c$ -tagging efficiency in Monte Carlo and scale factors

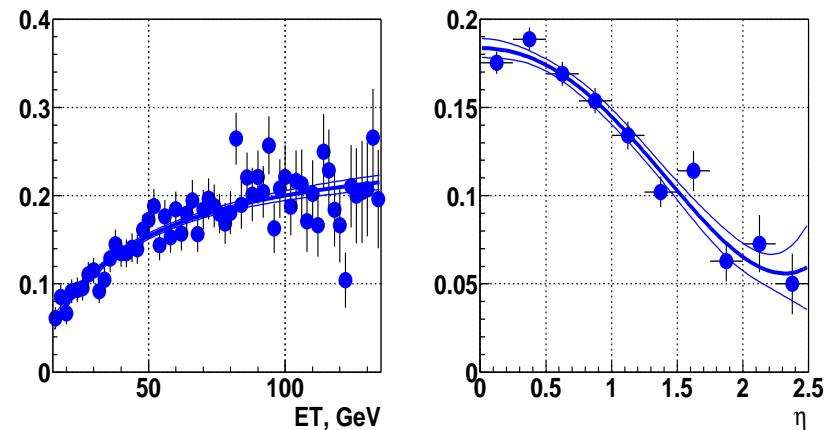
- what is measured in data is semileptonic  $b$ -tagging efficiency
- need inclusive  $b$ -tagging efficiency and inclusive  $c$ -tagging efficiency
- derive relevant scale factors on Monte Carlo

$SF_{b \rightarrow \mu}^b = \varepsilon_b / \varepsilon_{b \rightarrow \mu}$ : crucial, but close to 1 except for low jet  $E_T$

$SF_{b \rightarrow \mu}^c = \varepsilon_c / \varepsilon_{b \rightarrow \mu}$ : significantly different from 1, but does not affect much the result



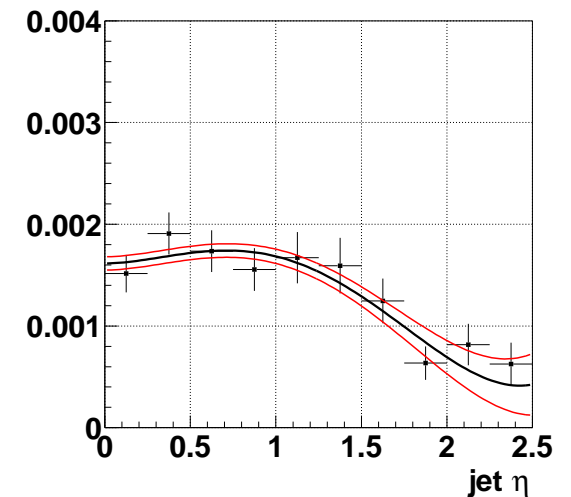
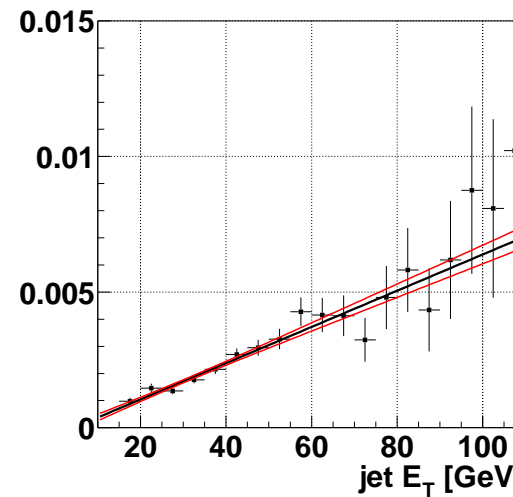
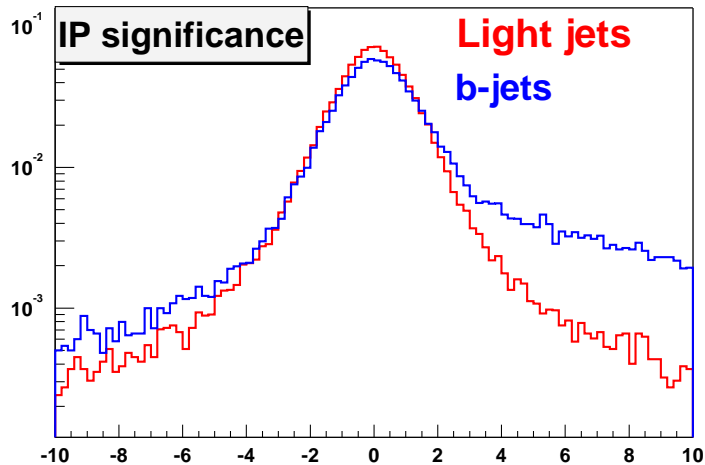
$b$ -tagging efficiency in MC (CSIP)



$c$ -tagging efficiency in MC (CSIP)

## Mis-tagging rate

- begin with negative inclusive tag rate  $\varepsilon^-$  measured in data
  - use negative side of DCA significance distribution (CSIP) or negative decay length (SVT)



mis-tagging rate (SVT)

- convert  $\varepsilon^-$  to light tag rate  $\varepsilon_l^+$  using scale factors determined on Monte Carlo:  $SF_l = SF_{ll} \times SF_{hf} \sim 1$ 
  - $SF_{ll} = \varepsilon_l^+ / \varepsilon_l^-$  (long lived particles and fakes)
  - $SF_{hf} = \varepsilon_l^- / \varepsilon^-$  (negative tag rate higher in HF jets)



## Summary of tagging probabilities

CSIP		
	one tag	$\geq 2$ tags
$t\bar{t} \rightarrow l + \text{jets}$	$45.9 \pm 0.8\%$	$15.8 \pm 0.3\%$
$W + \text{light jets}$	$2.60 \pm 0.06\%$	$0.03 \pm 0.01\%$

SVT		
	one tag	$\geq 2$ tags
$t\bar{t} \rightarrow l + \text{jets}$	$45.1 \pm 0.7\%$	$13.9 \pm 0.1\%$
$W + \text{light jets}$	$1.14 \pm 0.01\%$	$< 0.01\%$

probabilities to tag an  $e + \text{jets}$  event with at least 4 jets

## W+jets background

- the number of W+jets events after tagging  $N_W^{tag}$  is related to the number of untagged W+jets events  $N_W$  as

$$N_W^{tag} = N_W P_W$$

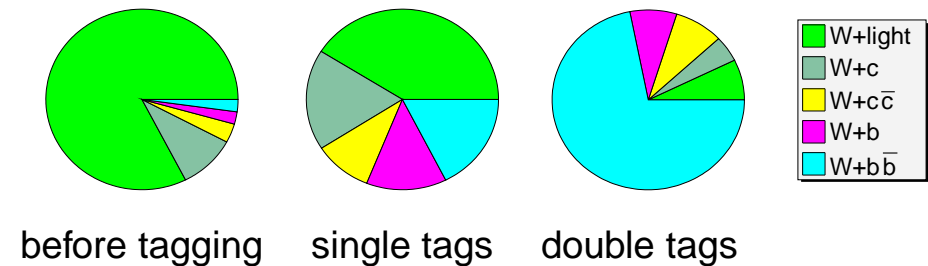
where  $P_W$  is average W+jets event tagging probability:

$$P_W = \sum_{flavor} F_{flavor} P_W(flavor)$$

- need to mix W+jets with different jet flavors in the right proportions

## How to get $F_{flavor}$ ?

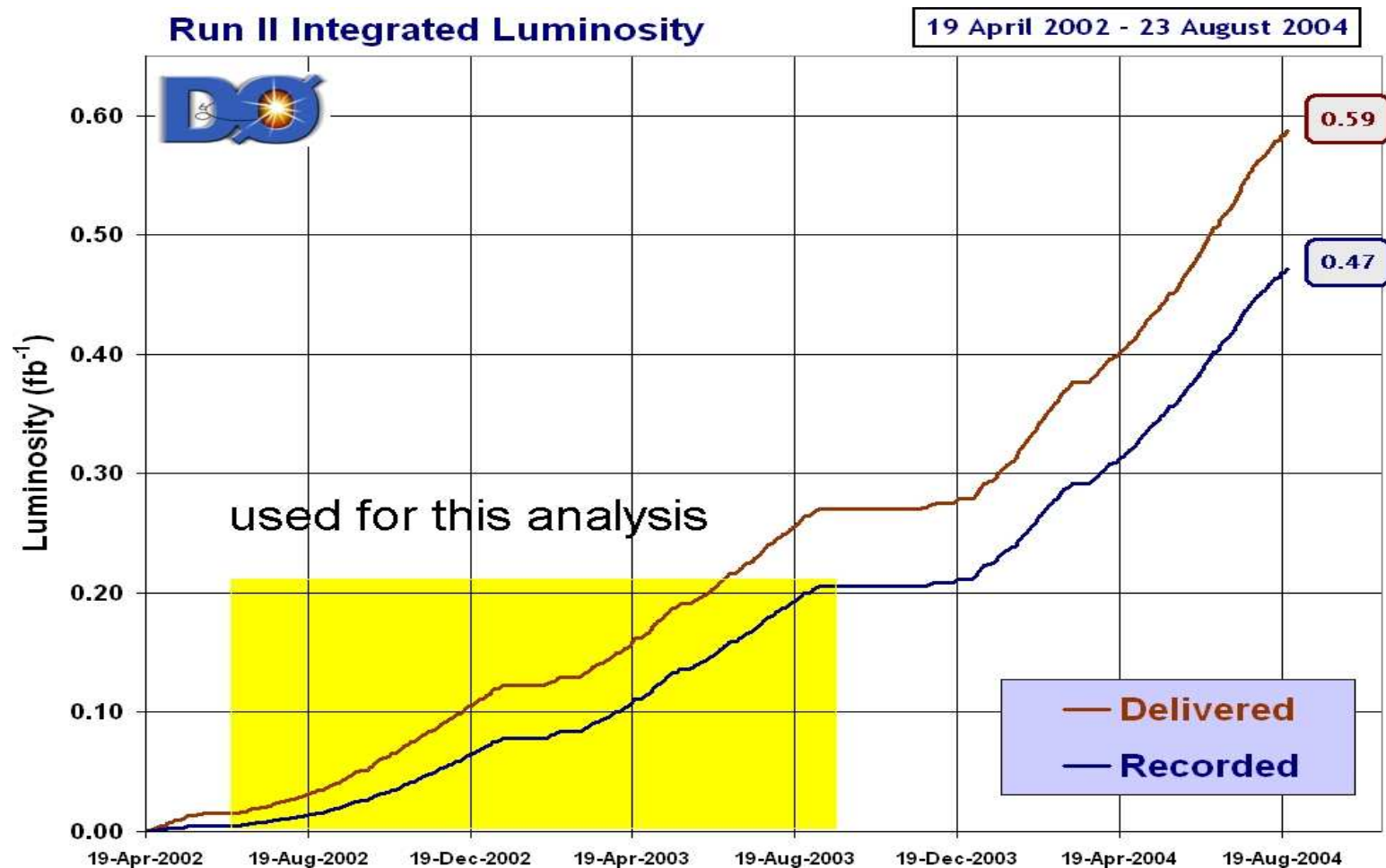
- use  $W$ +jets samples generated by ALPGEN 1.2 (CTEQ 6.1M) interfaced to PYTHIA 6.2 (CTEQ 5L)
- rely on the ratios of cross sections from Monte Carlo
- apply matching procedure to reduce double counting and sensitivity to parton generation cuts



Fractions of  $W$ +jets subprocesses with different flavors in  $e^+ \geq 4$  jets before and after tagging (CSIP)

Contribution	W+1jet	W+2jets	W+3jets	W+ $\geq 4$ jets
$Wb\tilde{b}$		$(0.87 \pm 0.05)\%$	$(1.34 \pm 0.09)\%$	$(2.20 \pm 0.17)\%$
$Wc\tilde{c}$		$(1.11 \pm 0.08)\%$	$(2.11 \pm 0.16)\%$	$(3.43 \pm 0.46)\%$
$W(b\tilde{b})$	$(0.69 \pm 0.02)\%$	$(1.23 \pm 0.04)\%$	$(2.00 \pm 0.08)\%$	$(2.27 \pm 0.82)\%$
$W(c\tilde{c})$	$(1.10 \pm 0.05)\%$	$(1.91 \pm 0.07)\%$	$(2.71 \pm 0.18)\%$	$(3.4 \pm 1.2)\%$
$Wc$	$(4.50 \pm 0.17)\%$	$(6.80 \pm 0.27)\%$	$(7.21 \pm 0.36)\%$	$(5.30 \pm 0.35)\%$
$W + \text{jets(mistags)}$	$(93.7 \pm 2.8)\%$	$(88.1 \pm 2.8)\%$	$(84.6 \pm 3.4)\%$	$(83.4 \pm 2.5)\%$

## Data sample: integrated luminosity



- this analysis:  $169 \text{ pb}^{-1}$  ( $e$ +jets),  $158 \text{ pb}^{-1}$  ( $\mu$ +jets)
- now we have recorded  $\sim 500 \text{ pb}^{-1}$

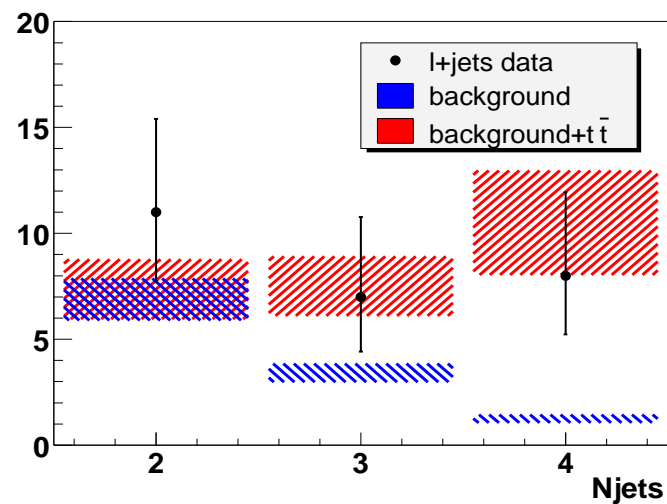
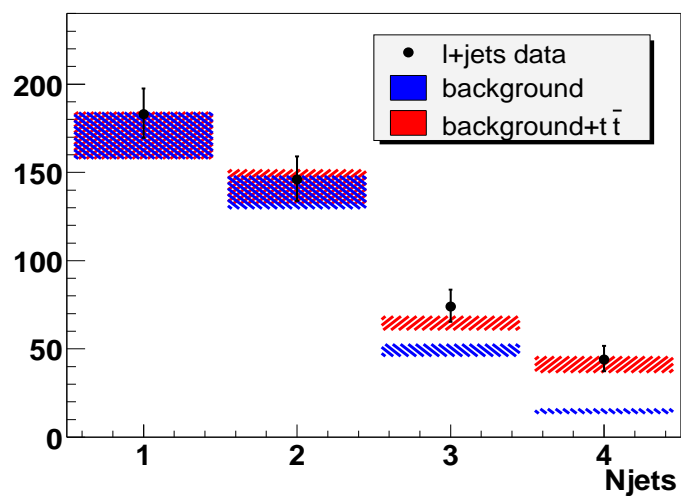
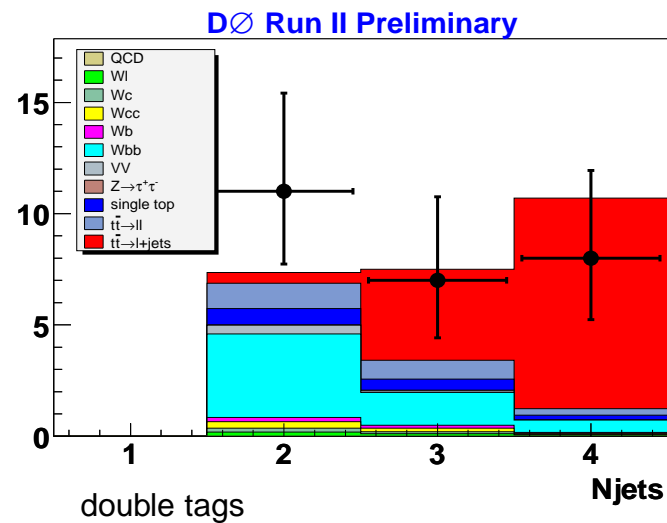
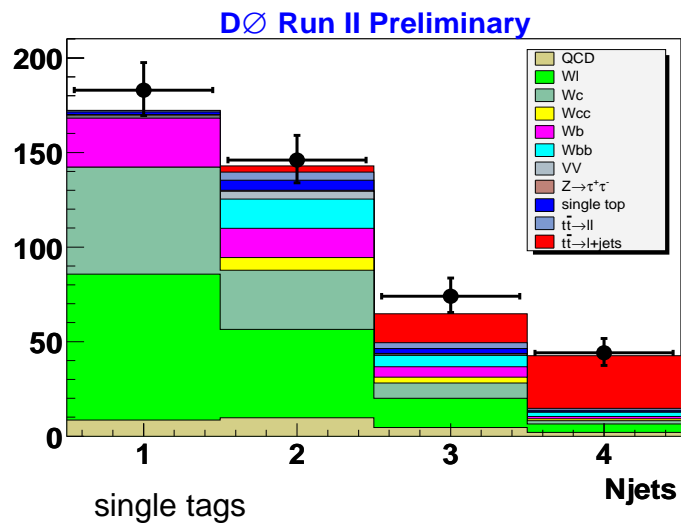
## Data sample: the number of events

	W+1jet	W+2jets	W+3jets	W+ $\geq$ 4jets
preselected	11586	4455	1105	295
CSIP: tagged	183	157	81	52
double tagged		11	7	8
SVT: tagged	119	128	76	49
double tagged		8	8	6

- work with four jet multiplicity bins
  - bins 1,2: use to control the background
  - bins 3,4: extract the  $t\bar{t}$  production cross section
- cross section is extracted from a simultaneous likelihood fit to eight separate channels:
  - $e$ +jets and  $\mu$ +jets
  - events with 3 and  $\geq 4$  jets
  - single and double tagged events

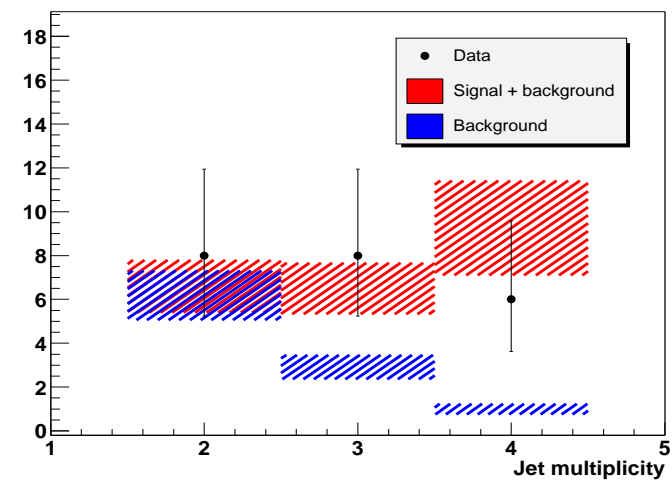
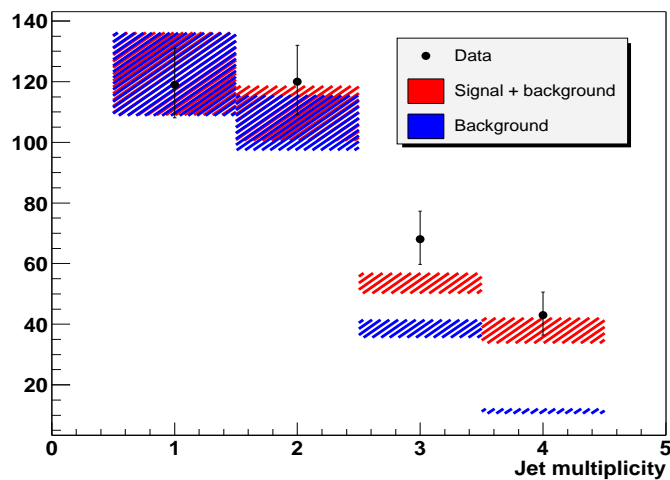
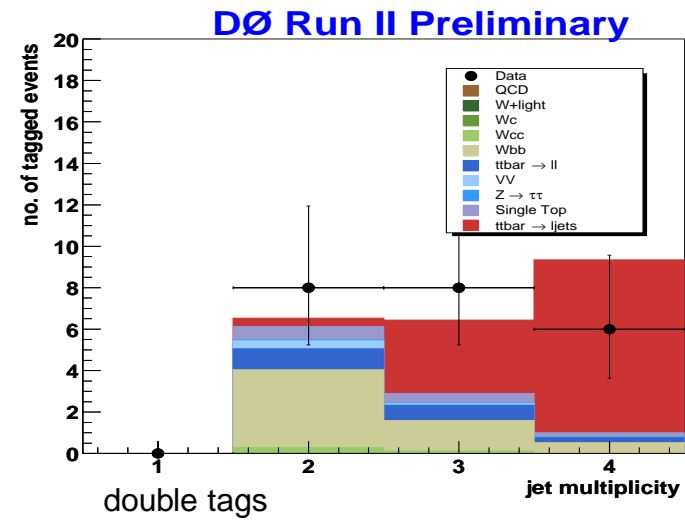
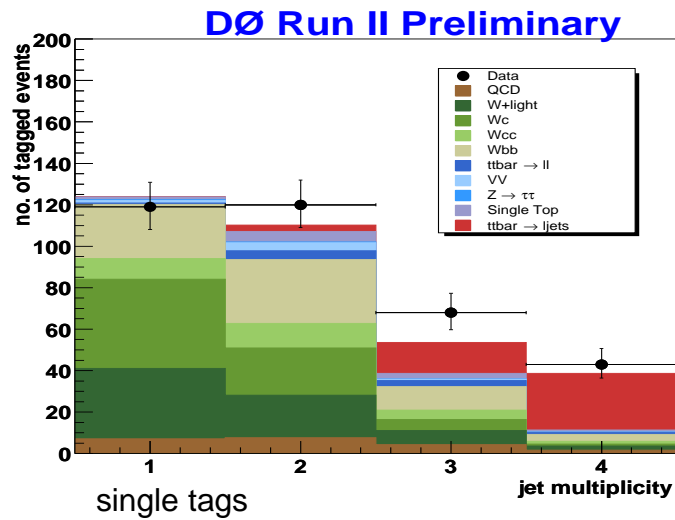
# Observed vs predicted number of events: CSIP

signal prediction is shown for  $\sigma_{t\bar{t}}=7$  pb



# Observed vs predicted number of events: SVT

signal prediction is shown for  $\sigma_{t\bar{t}}=7$  pb



## The result

CSIP:  $\sigma_{t\bar{t}} = 7.2_{-1.2}^{+1.3} (\text{stat}) {}_{-1.4}^{+1.9} (\text{syst}) \pm 0.5 (\text{lumi}) \text{ pb}$

SVT:  $\sigma_{t\bar{t}} = 8.2_{-1.3}^{+1.3} (\text{stat}) {}_{-1.6}^{+1.9} (\text{syst}) \pm 0.5 (\text{lumi}) \text{ pb}$

theoretical prediction (NNLO):  $6.77 \pm 0.42 \text{ pb}$  (hep-ph 0309045)

- correlations / combination of taggers under study
- for each tagger, 60% of tags are also found by another one



## Sources of systematics

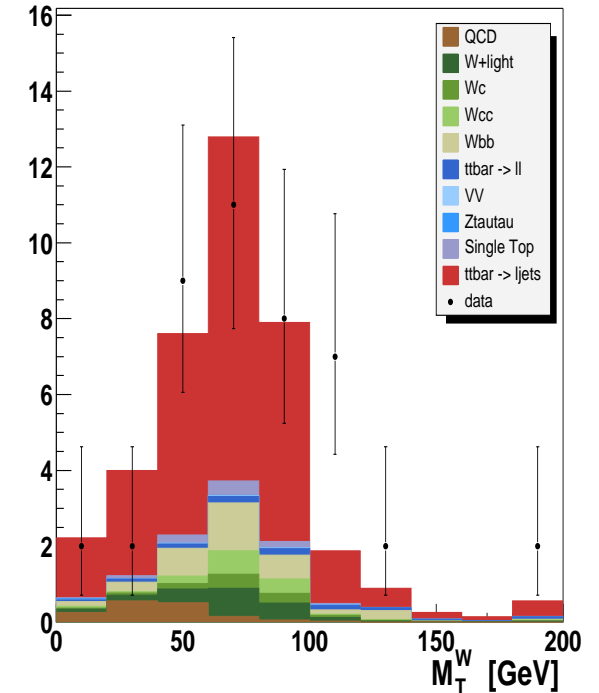
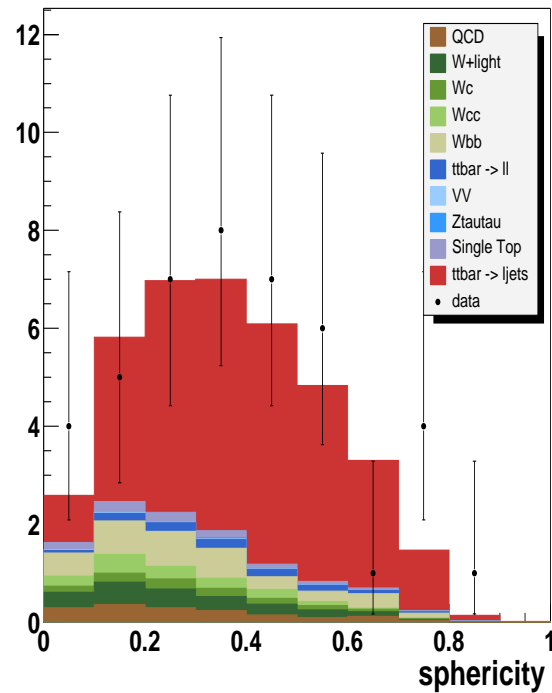
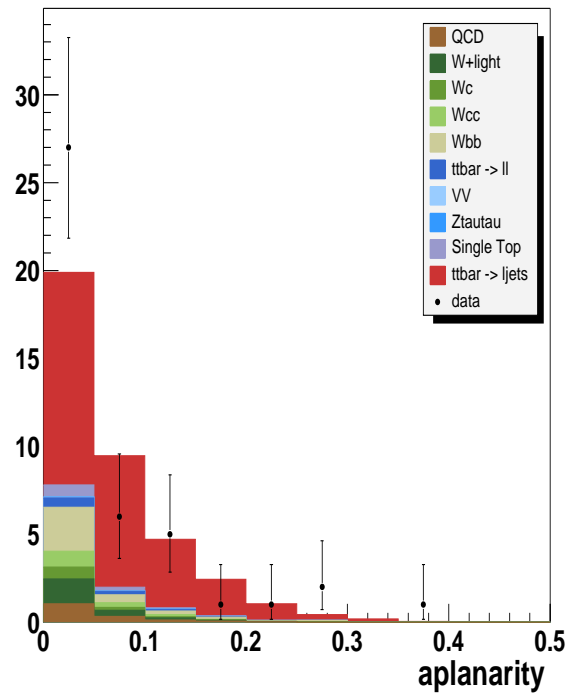
- main sources of systematics:

- jet energy scale,  $\Delta\sigma_{t\bar{t}} \sim 1 \text{ pb}$
- $b$ -tagging efficiency in data,  $\Delta\sigma_{t\bar{t}} \sim 0.9 \text{ pb}$
- $W$  fractions,  $\Delta\sigma_{t\bar{t}} \sim 0.8 \text{ pb}$

- full list of systematic uncertainties:

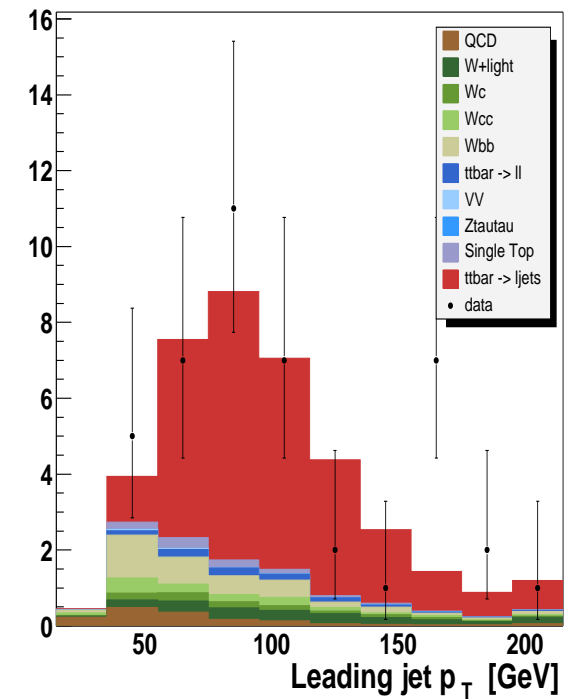
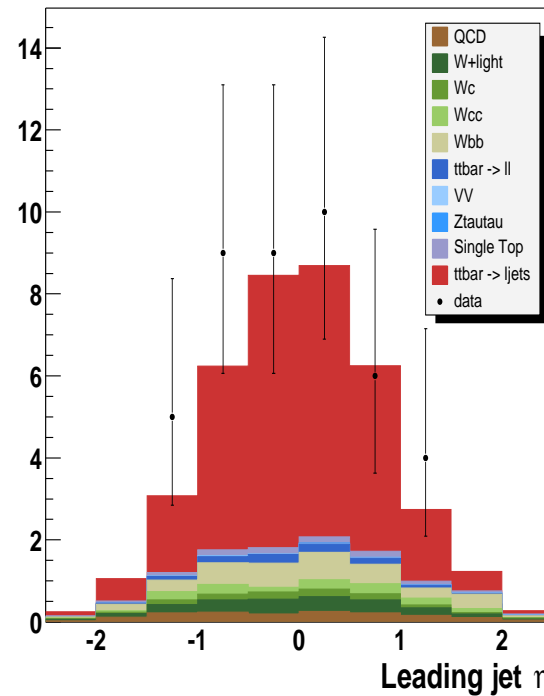
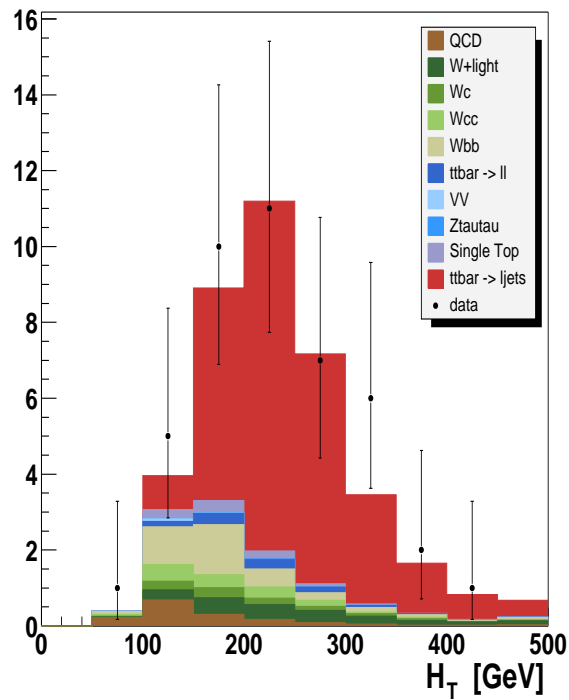
- $W$  fractions
- trigger efficiency
- primary vertex efficiency
- matrix method efficiencies
- object ID efficiency
- jet resolution
- jet energy scale
- heavy flavor tagging efficiency in MC
- semileptonic  $b$ -tagging efficiency in data
- taggability
- negative tag rate and light flavor SF
- fragmentation model
- assumption  $SF_b = SF_c$
- top mass

# Cross-checks: aplanarity, sphericity, transverse $W$ mass



shown for SVT

# Cross-checks: scalar sum of jet energies, leading jet $\eta$ and $p_T$

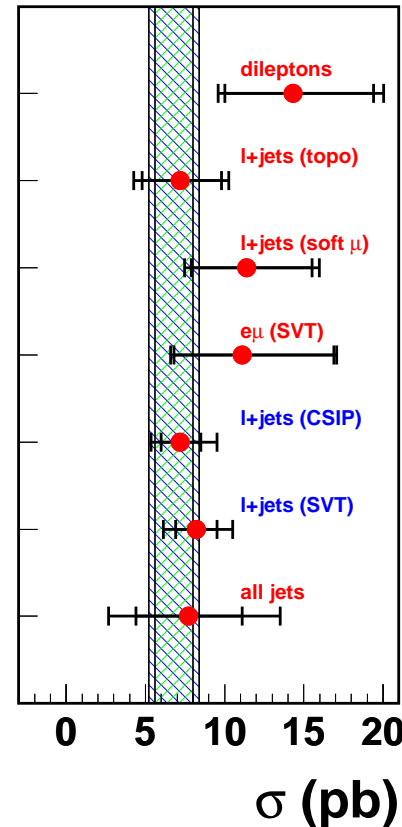


shown for SVT

## Conclusions

- we have measured the  $t\bar{t}$  production cross section in lepton+jets channel with lifetime  $b$ -tagging
- two different methods were used to cross-check results
- this is the most precise measurement of the  $t\bar{t}$  production cross section in DØ
- the result is in a good agreement with the Standard Model prediction

DØ Run II Preliminary



- the quoted systematic error is conservative, expect significant improvement
- now have 2-3 times more data, can reduce statistical and many systematic errors